LBNL 6715 E

BERKELEY LAB
Lawrence Berkeley National Laboratory

Lawrence Berkeley National Laboratory

Enabling Broad Adoption of Distributed PV-Storage Systems via Supervisory Planning & Control

Nicholas DeForest[1], Michael Stadler[1,2], Gonçalo Cardoso[1], Tobias Brandt[1,3], Sankar Narayanan[4]

[1]Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA
[2]Center for Energy and Innovative Technologies, Doberggasse 9, A-3681 Hofamt Priel, Austria
[3]University of Freiburg, Platz der Alten Synagoge, 79085 Freiburg, Germany
[4] Tri-Technic, 185 S. Fairview Lane, Sonora, CA 95370, USA

Published in ACEEE Summer Study on Energy Efficiency in Buildings 2014, Asilomar Conference Center Pacific Grove, CA, 2014

June 2014

Parts of this work has been financed by the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy under Contract n° DE-AC02-05CH11231

Disclaimer

Enabling broad adoption of distributed PV-storage systems via supervisory planning & control

Nicholas DeForest[1], *Michael Stadler*[1, 2], *Gonçalo Cardoso*[1], *Tobias Brandt*[1,3], *and Sankar Narayanan* [4]
[1]*Ernest Orlando Lawrence Berkeley National Laboratory*
[2]*Center for Energy and Innovative Technologies, Austria*
[3]*University of Freiburg, Germany*
[4]*Tri-Technic, Sonora, California*

ABSTRACT

This paper demonstrates the economic benefits of using of day-ahead optimization and real-time control to plan and implement charging/discharging schedules for a behind-the-meter system comprised of PV generation and electric storage in commercial buildings. With investment costs falling over the past decade, distributed PV has become an increasingly attractive option for commercial buildings seeking to reduce energy costs. However, because PV is inherently intermittent, it cannot actively manage time-of-use tariff demand charges or respond to real-time prices or demand response signals. Missing out on these economic benefits amounts to a significant loss in value for the PV system. By pairing PV with electric storage and optimized control, commercial customers can begin to capture these benefits, leveraging synergies by storing energy from periods of excess PV generation and discharging as needed in other periods. Optimal planning of charging behavior is essential to the controller and ensures that complex cost and performance trade-offs are all duly considered and storage schedules are cost-minimal. The presence of the controller also reduces customer impact on the wider electricity grid, by granting customers a level of control over power flow to and from the grid. The potential economic benefits of this system may help PV and storage overcome their largest barrier—investment cost—while reducing the impact of wide-spread PV adoption for utilities, by creating more flexible, better integrated customer loads and generation. This paper shows that optimized control for PV-storage systems increases the annual energy cost savings by as much as 25% with significant increases to net-present-value for a real California facility under a commercial time-of-use tariff.

INTRODUCTION

Over the past decade, capital costs of installed photovoltaic (PV) systems have fallen significantly, at an average rate of 5% to 7% per year, from \$12 per W_{DC} installed in 1999 to an estimated \$2 to \$4 per W_{DC} in 2014 for systems above 220 kW, according to the U.S. Department of Energy SunShot Initiative (Feldman et al 2012). Given the strong downward trend on PV investment costs, it is not surprising to find that installation of distributed commercial and residential scale PV systems has accelerated dramatically in recent years. According to industry reports, over two thirds of distributed PV capacity has been installed over the past two and a half years. Industry experts expect this trend to continue, with total installed capacity of distributed PV doubling in the next two and a half year (SEIA 2013). While higher penetration of renewable generation, such as PV, is widely seen as a positive development, it is understood that as installed PV capacity grows, new problems arise. By its nature, PV is intermittent and cannot be actively dispatched. While PV generation will typically be available during high-demand midday periods, its output can be subject to large fluctuations over short time periods. Given the instability that high penetration of distributed PV can introduce, additional supporting technologies, in the form of spinning reserves, storage on the grid-side, or local, distributed storage behind the meter will be needed to ensure that sufficient supply is always available to meet system load. As PV penetration increases, the size of this requirement will grow commensurately, creating an additional, external cost not included in the capital cost of PV.

Beyond uncertainty in daytime PV generation, additional problems exist. Even under ideal insolation conditions, PV output will taper off in the afternoon as the sun begins to set. In many regions, this corresponds with the time when system loads naturally tends to peak, as many people return home and begin to engage in energy-intensive activities. These two drivers converge to create the potential for conditions where non-PV generators will need to ramp up output much more quickly than currently required, to make up for the increasing demand and decreasing supply from PV. The threat associated with rapidly transitioning from PV to conventional energy sources is so widely understood, it is often referred to colloquially as the “duck chart” (Figure 1). Taking this figure as an example, as total generation from PV increases over the next 7 years, the average afternoon system ramp rate grows from approximately 1.8 GW per hour in 2013 to 4.2 GW per hour. Currently this requirement will often be met by dispatching peaking units that can switch on quickly to meet increased afternoon demand (high ramp rates, but high operation costs), but with the total system ramp rate projected to more than double, simply expanding this approach may become prohibitively expensive.

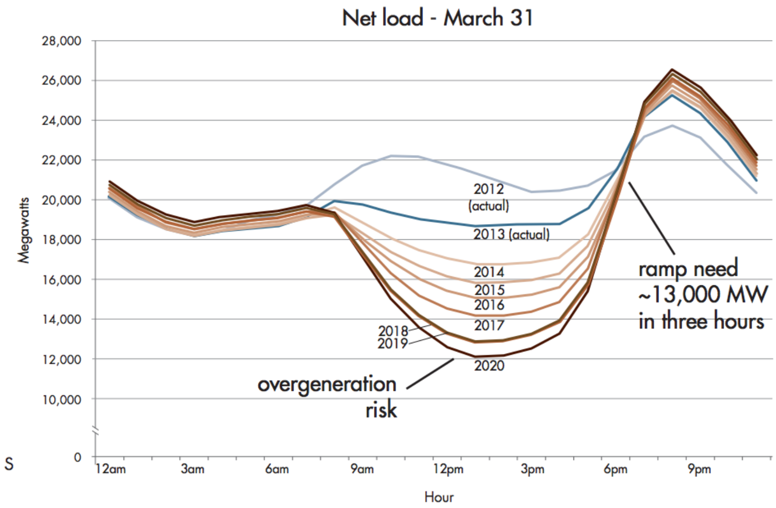

Figure 1. The “duck chart” illustrates how increasing penetration of PV generation can produce progressively higher ramp rate requirements in the afternoon, when total demand increases, but PV generation begins to taper off. *Source*: CAISO 2013

If these trends persist without solutions to mitigate their impact, the economic conditions for additional, grid-friendly PV deployment will become less and less favorable to further investment. From the grid perspective, additional investments will be needed, either in the form of high ramp-rate generators or storage buffers to increase the upper-bound for grid-friendly PV deployment. If distributed storage and control of commercial and residential scale PV generation can be implemented behind the customer meter, then, along with the appropriate customer outreach and controller deployment, the utility can drive more grid-friendly behavior via simple price signals. Such a solution could contribute to alleviating the aforementioned problems while PV penetration is still relatively low and PV-related problems are not yet disruptive.

The Case for PV-Storage Systems

The economics of a PV-storage system will be different from the perspective of a customer. Depending on the amount of PV generation vis-à-vis the customer’s load, the details of the customer-utility agreement, and the technology, a number of scenarios emerge. Illustrative examples of typical daily load and electricity supply profiles are given for a small subset of these scenarios in Figure 2.

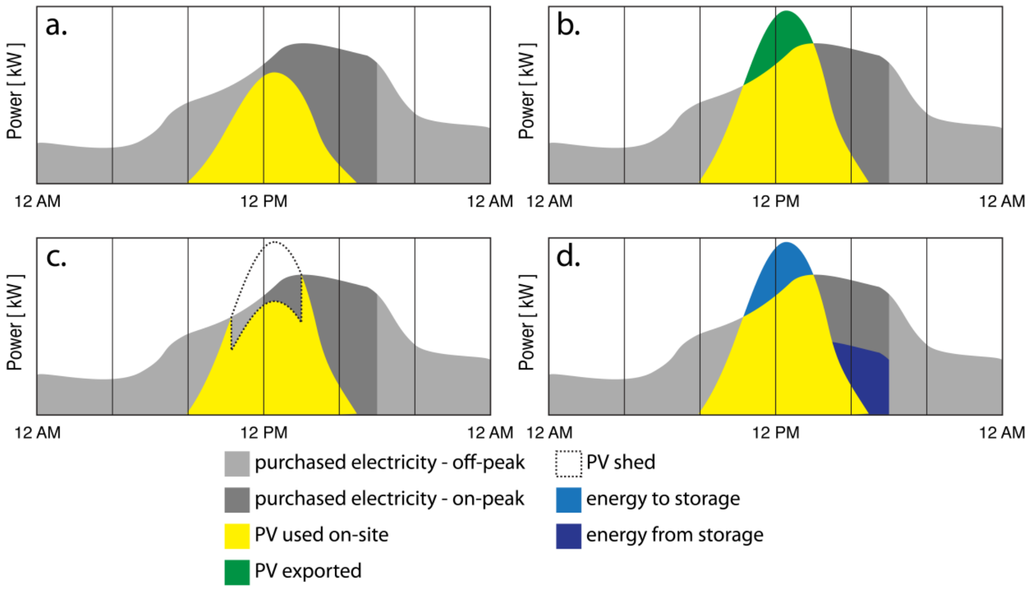

Figure 2. Illustration of daily load and generation profiles for PV generation scenarios

a. **PV output never exceeds building load** – This represents the simplest case. If PV generation never exceeds customer load, then it can always be used to directly serve a portion of that load. Because the generation is used when available, the customer has no levers to affect the economics of the PV generation. For instance, under many TOU tariffs, demand charges can make up a substantial portion of total electricity costs. These demand charges can be determined for the entire month by periods as small as 15 minutes. If PV output begins to taper off during the "on-peak" period of such a tariff, then a large portion of potential cost savings will be lost for the billing cycle. By that same logic, the customer is also unable to respond to real-time price signals, which also undermines the value of PV deployment.

b. **PV output exceeds building load, utility allows for export** – As the size of the PV system increases, relative to load, export conditions will eventually arise. Under a favorable agreement with the utility, the customer will be able to export excess generation back to the utility and possibly generate additional revenue under a feed-in tariff or a similar agreement. This revenue stream may incentivize customers to install larger PV systems than would be economically viable otherwise. As with scenario a, the customer cannot actively modulate net load supplied by the utility, and therefore, is not capable of managing demand charges. Similarly, the customer does not have any ability or incentive to adopt behavior to mitigate the problems caused by the rapid growth of distributed PV generation.

c. **PV output exceeds building load, utility restricts export** – To counter the problem of PV over-generation, utilities may move to less accommodating agreements with customers, by limiting or altogether prohibiting the export of excess PV generation back to the grid. When approaching this limit, the only lever available to the customer is PV curtailment. This curtailment process is inefficient, and may only be possible in discrete segments, such that a quarter, half, or even all PV output must be switched off while over-generation conditions exist. In addition to the factors outlined in scenarios a and b, this creates unfavorable economic conditions, in particular, for relatively large, distributed, behind-the-meter PV systems. This approach also does not remove the threat of instabilities for utilities, as customers approaching their export limits will need to quickly shed PV generation, potentially producing sudden and unpredictable spikes in demand.

d. **PV output exceeds building load, electric storage is present** – In the case of the fourth scenario, storage in the form of a stationary electric battery is present behind the customer meter. Under either the feed-in tariff or non-export agreement, the customer can select to store excess PV generation and discharge storage at times when it is most economically advantageous to do so. This could be done for demand-charge management under a TOU tariff, as shown in Figure 2d, or in response to other real-time price signals. While the additional presence of a battery increases total system cost and complexity, if properly implemented it will improve overall economic performance of PV systems and potentially enable customers to engage in a new revenue stream (e.g. demand response.)

Paired with storage, customers will have the ability to actively respond dynamically to price signals, meaning that utilities can create programs to incentivize particular behaviors which help to reduce peak conditions and excessive ramp rates at the system level, improving reliability across the grid. In addition to the peak-shaving behavior illustrated in Figure 2d, a PV-storage system also provides customers with the potential for improved local reliability. In the event of short outages, customers can employ storage to serve all or critical loads, until service is restored. Seamless switching between grid-connected and grid-disconnected (islanded) modes can be implemented to minimize disruptions during such events. With sufficient storage capacity, such a system could act as a microgrid, islanding more frequently, in order to maintain maximal reliability and reduce variation in voltage and frequency serving critical loads. The local PV-storage system simply needs a supervisory controller to instruct local distributed energy resources (DER). The controller would receive price signals and information from external sources; use that information to generate load and PV forecasts; optimize dispatch instructions, subject to technology constraints; then implement the planned schedule on a real-time basis, taking into account deviations from forecasted information. The logic for all the aforementioned behaviors could be programmed into this controller to ensure that total utility costs remain low, and reliability metrics are all being satisfied.

Details of the Supervisory Controller

The economics of a distributed PV-storage system will not be determined solely by the price inputs, but also by how quickly the system can adjust to changes in load, generation and price signals to ensure charging, discharging and utilization behaviors capture as much economic benefit as possible. In other words, a smart and adaptive supervisory control layer is essential to the success of such a system. It is just such a controller that researchers at Lawrence Berkeley National Lab (LBNL) are currently developing. This controller will leverage the pre-existing optimization functionality of DER-CAM (Distributed Energy Resource Customer Adoption Model). DER-CAM is a mixed integer linear programming model used to inform decision making regarding DER investment and operations (Marnay et al. 2013). Developed over the past decade, DER-CAM has been applied to a diverse number of research questions, including assessing the potential for combined heat and power (CHP) units (Stadler et al. 2009) and thermal energy storage (TES) deployment (DeForest et al. 2014), day-ahead scheduling of battery storage at the Santa Rita Jail microgrid (Cardoso et al. 2013), and automated day-ahead scheduling of thermal resources at a University of New Mexico campus building (Mammoli et al. 2013).

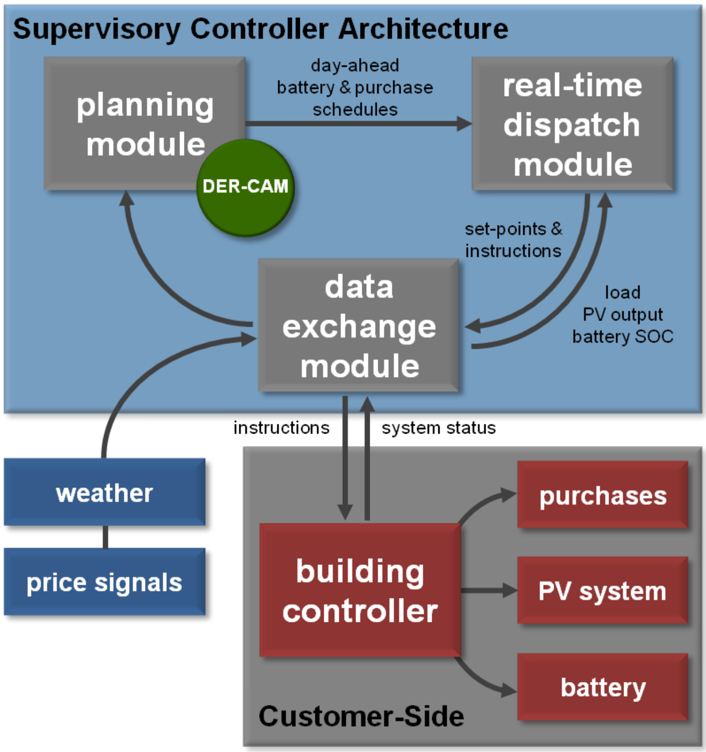

Figure 3. Diagram of supervisory controller for PV-storage systems

The original instance of the model, known as Investment & Planning DER-CAM, was built to select the optimal portfolio of DER technologies for a given site, based on historic site load data (typical one year or more), DER investment costs and technology constraints. As a supplement to this, LBNL has also developed Operations DER-CAM to address more detailed question of DER-CAM operations and scheduling. Operations DER-CAM uses the preexisting DER portfolio of a specific site as an input, as well as forecasts of loads and weather conditions, rather than historic data. Operations DER-CAM determines optimal dispatch schedules for DER technologies for day-ahead and week-ahead time horizons. Operations DER-CAM will be used within the supervisory controller for in-advance planning of battery schedules. Details of Operations DER-CAM can be found in (Marnay et al. 2013).

The supervisory controller can be better understood by exploring the internal modules, their functions and their internal and external interactions, as shown schematically in Figure 3. This figure is not intended to detail the configuration of the system (e.g. placement of inverter relative to storage and other DER), however the supervisory controller is agnostic in this regard, and can be adjusted to site-specific configurations.

The first is the **data exchange module**, which simply facilitates communication between the supervisory controller, the customer's controller and other external data sources. It translates instructions coming from the real-time dispatch module into set-points, which regulate the net electricity purchases, outputs from the PV system, battery and whatever other DER is present at the site. It collects real-time status of equipment and load to feed back to the controller to update forecasts and improve planning. The data exchange module also collects data on weather forecasts and price signals from external sources.

These data are fed into the **planning module** of the controller. The planning module is where the DER-CAM optimization resides. It uses forecasters based on analysis of historical load data, as well as forecasted data for pertinent drivers, such as weather and occupancy estimates, to predict total electricity loads and PV output for the next 24 to 48 hours. Using these forecasts, details of electricity tariff rates and structure and technical constraints of the DER equipment, DER-CAM is able to determine an optimal schedule for battery charging/discharging and net electricity purchases. Of course, the use of these day-ahead instructions is only optimal so long as the forecasted data and regression model accurately represent the next day's events. This will not always be the case. To account for this, the optimized schedule is delivered from the planning module to the **real-time control module**, and serves as a preliminary guide for DER outputs.

The real-time control module, taking this schedule into account, is equipped with a number of heuristics on how to respond when actual load or generation values deviate from the forecast. Because DER-CAM optimization run-time prevents the planning module from directly instructing the DER, the quick and simplified decision-making of the real-time module is essential. In its completed form, the real-time module will continuously feed current status information back to the planning module, which in turn will be producing updated "optimal" schedules at hourly (or sub-hourly) intervals to account for changes in load and generation conditions.

Forecaster Details

The forecaster that supplies the necessary data to the optimization tool employs two different methods. Clear sky photovoltaic generation for a given time is calculated using a linear regression model that links sun altitude and generated power and slowly adapts over time. Specifically, data on the past 30 hours with clear sky and altitude angles larger than zero degrees is used to determine the regression coefficients $\widehat{\beta_0}$ and $\widehat{\beta_1}$. Site location is used to determine altitude angles (ϕ_t) for the following 24 hours. Equation 1 illustrates that expected generation E is set to zero if these angles are less than zero. Otherwise, expected power is determined based on the regression coefficients and the angles. Additionally, it is multiplied by a factor δ, which represents seasonal patterns that influence solar radiation as outlined in Masters (2004). This factor starts at 1, but is slightly adapted whenever the deviation between a predicted and an actual value exceeds a certain threshold.

$$E(P_t) = \begin{matrix} \delta[\beta_0 + \beta_1\phi_t] & \text{if } \phi_t \geq 0 \\ 0 & \text{otherwise} \end{matrix}$$

This learning mechanism can also be found in the load forecaster, although it is built around a different method. Since the load exhibits strong recurring patterns for each day of the week (with the exception of holidays, which are similar to Sundays), a Fast Fourier Transformation (FFT) is used to extract the dominant frequencies composing these patterns. For instance, to predict next Tuesday, a FFT of the three past Tuesdays is performed. These very stable patterns only vary when the occupancy of the base changes. To compensate this, a scaling factor is included in this forecaster, as well. Similar to the factor in the PV forecaster, it starts at 1, but is adapted when deviation exceed a threshold(Brandt et al. 2014).

Site Details

The development of this supervisory controller is currently ongoing for use at a large California facility equipped with 2 MW of PV and stationary storage sized at 1 MWh. Electricity demand at the facility reaches its annual peak of 2.56 MW in August. At this point in the project, the controller has not yet been deployed at the site, and real operational data on performance of the controller has not yet been collected. Real data will be important to assess in particular how accurately day and hour ahead forecasts represent real load and insolation profiles at the site. Additionally, the effectiveness of the real-time control module, based on how well it can respond to such deviations, can only be assess once real operational data has been collected. However, the value of such a supervisory controller can be estimated using DER-CAM simulation of a typical year of load and PV generation data. The details and findings of this simulation are given in subsequent sections.

METHODOLOGY

To evaluate the economic benefit of a supervisory controller for a PV-storage system, the Investment & Planning DER-CAM model is employed. While this is not the version of DER-CAM that will be employed in the actual controller, it gives a general, annual perspective on operating the PV-storage system based on optimized schedules. This planning tool could be applied to optimize the capacities of both PV and storage, however for this application those capacities are fixed as inputs. DER-CAM will simply be used to determine cost-optimal scheduling of storage under the varying load and weather data of a typical year. The model simulates 3 typical load profiles (weekday, weekend, peak day) and typical weather data for each month, resulting in 36 total simulated day-types. A storage charging/discharging profile is determined for each of these days. The daily electricity consumption profiles are then scaled to a monthly value, at which point the electricity rate structure is applied, to determine monthly electricity costs. The objective function of the optimization is to minimize the annual electricity costs of the site. Other costs, such as operations and maintenance costs are not considered in the optimization objective function. Capital costs for equipment installation are considered in net present values (NPV) calculations, which examine annual costs and savings over the equipment lifetime. NPV present in this paper does not include other revenue opportunities such as demand response.

To capture the effect of real test-site constraints, PV exports are limited to 1 MW. Additionally, when PV curtailment becomes necessary, it must be done in 25% increments, which corresponds to disconnecting an entire array. Given the importance of electricity costs in the objective function, and given the TOU tariff structure, the optimization will favor storage behaviors that minimize PV curtailment and reduce power demand charges. Other incentives, such as demand response, can also be characterized and included in the objective function. However, this simple example presents only tariff electricity charges and revenue from PV export. The tariff applied to this investigation is Pacific Gas and Electric's Industrial E-20 rate (PG&E 2014). The tariff includes demand charges in on-peak and mid-peak periods, as well as a non-coincident demand charge which is applied to the maximum monthly demand. These demand levels are calculated from the highest 15-minute average consumption at any point in a specified period (e.g. on-peak or mid-peak). PV export is paid the current TOU energy rate (i.e. net-metering).

Insolation and temperature profiles are generated from historic typical meteorological year (TMY) sources for the site location. These are necessary to determine hourly PV output and efficiency. Hourly load profiles are based on a statistical analysis of the test site historic meter data over the past few years. In practice, extensive historic data is valuable but not critical for building and calibrating load forecasters for the controller.

Scenarios

To assess the value of optimization, the results of the DER-CAM optimization are compared with a simple scheduling heuristic. The heuristic has no ability to anticipate future conditions, and formulates charging instructions based only on current conditions. This heuristic is structured to prevent the PV system from being curtailed whenever possible. Under the heuristic, storage starts each day at the minimum SOC. It is charged when PV generation exceeds both the local load and the 1 MW PV export limit. Under these conditions, the charge rate is constrained by the available excess PV generation, the power limits and the empty energy capacity of the battery. Under conditions when PV generation is less than local load, and useable energy remains in storage, the battery discharges to reduce grid electricity purchases. This discharge rate is constrained by the net difference between load and PV generation, the amount of usable energy in the battery and the maximum discharge limits.

These two scheduling methods (DER-CAM optimization and the simple heuristic) are applied to a number of different technology scenarios. The base case scenario has no installed PV or storage, and is simply the cost of meeting local loads directly with grid electricity. Scenarios 1-3 have PV systems sized at 1, 2, and 3 MW respectively and no storage. Scenarios 4-6 have similarly sized PV arrays and 1 MWh 0.5 MW of storage. Scenarios 7-9 again have similarly sized PV arrays and 2 MWh 1 MW of storage. These inputs are summarized in Table 1. For scenarios with onsite storage (S4-S9), both simple and optimal schedules are generated.

Additional NPV inputs such as interest rates and capital costs for each DER are important to determine the economic viability of any installation, though are not necessary for constructing or operating the controller. The capital cost for PV installation is assumed to be \$3150 per kW with a lifetime of 20 years. Storage costs will also have a significant impact on the total system cost. Currently, storage technologies are likely too expensive to realize economic benefits in most applications. However, with growing interest in using distributed storage for these types of applications, the per kWh price of storage may see a rapid reduction similar to that experienced by PV over the past decade. To capture the sensitivity of system economics on storage price, three cost scenarios will be explored. The first present prices that are comparable to current values \$1000 per kWh. The next is an optimistic level of \$500 per kWh. Finally, a highly optimistic scenario of \$200 per kWh, in line with recent California Energy Commission research targets (CEC 2014). A lifetime of 20 years (approximately 5000 cycles) is assumed for each of these scenarios. Finally, an interest rate of 5% is used for amortized cost and net present value calculations. Changes in these two parameters could have significant impact on the overall economics of the system, but a sensitivity analysis of these has not been performed for this analysis.

RESULTS & DISCUSSION

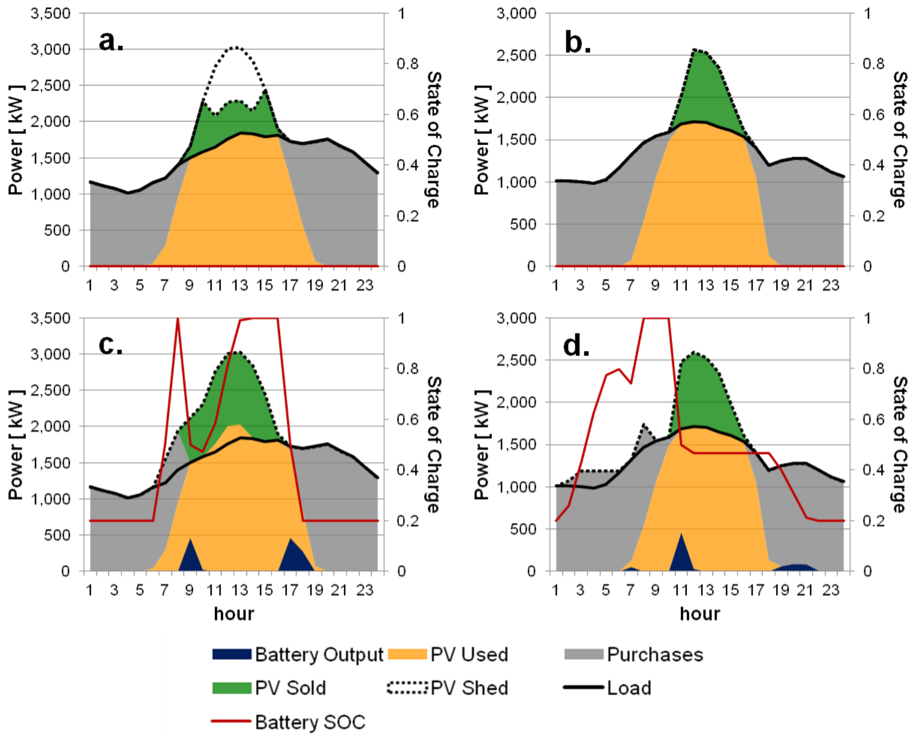

Figure 4. Example optimized schedules from DER-CAM show results for scenario 3 (no storage) for a typical July weekday (a) and March weekday (b) and Scenario 6 (with storage) for July (c) and March (d). Simple schedules for these scenarios are not shown.

For each of the 36 day types simulated, DER-CAM generates a profile of usage for the battery and PV, subject to all power balance and export constraints. Examples of these usage profiles can be seen in Figure 4, which shows the results for typical July and March weekday for scenario 3 (a, b), which has no installed storage and scenario 6 (c, d), which includes 1 MWh of storage. The charging/discharging strategy employed by the optimization will vary depending on the specific balance between local load and available insolation. As Figure 4a indicates, PV generation exceeds both local loads and the export limit, requiring curtailment. When optimized storage is introduced (Figure 4c) that excess generation can be sent to storage and curtailment can be avoided. During other times, the optimized storage strategy is less intuitive. During typical March weekdays (4b, d), PV generation does not exceed the export limit. Rather than remaining empty until midday, storage is charged in the morning with grid electricity. Storage is discharged on-peak, which allows a greater portion of the PV generation to be exported when TOU energy rates are at their highest.

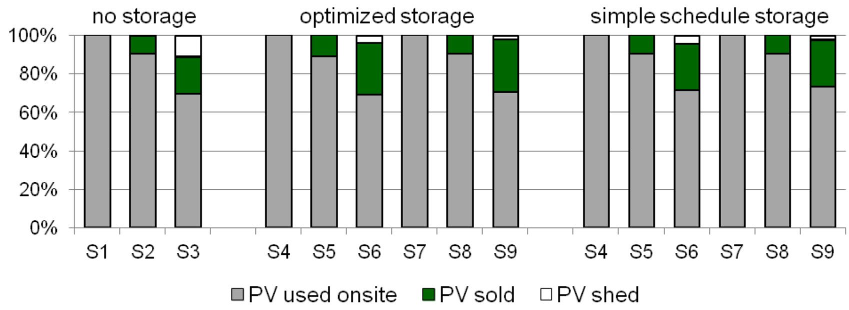

Figure 5. Annual PV capacity factors for onsite use, export and shed PV generation for each scenario (S1-S9). S4-S9 are scheduled separately with DER-CAM and the simple heuristic.

The effectiveness of the optimization can be assessed by a number of metrics. Because sub-optimal behavior risks higher incidence of PV curtailment, the overall PV capacity factor (i.e. the fraction of the time the full PV output is being used onsite or sold) gives some indication. Figure 5 shows the annual fraction of total PV used, sold, and shed by each scenario. For scenarios with only 1 MW of PV (1, 4, 7) all generation can be used directly onsite. As the PV capacity increased to 2 MW (2, 5, 8) nearly 10% of the PV is exported. This is true independent of storage size and scheduling method. At 3 MW of PV (3, 6, 9), curtailment becomes necessary. As storage increases the overall fraction curtailed decreases from 11% with no storage to 4% with 1 MWh to 2% with 2 MWh. Interesting, there appears to be no difference in total curtailment between the optimized and simple scheduling methods.

The economics of these two methods are however significantly different. Table 1 gives a summary of results for each technology, schedule and cost scenario. Examining the annual costs savings, the optimized schedule produces savings that are 5% to 25% higher than the corresponding simple heuristic case. While these two methods utilize a similar amount of onsite PV generation, only the optimization is able to maximize the revenue from PV export, while also managing monthly demand charges with strategic discharging of storage.

Intuitively, as total PV and storage system sizes increase, the total annual savings increase. However, the benefits do not necessarily increase commensurately with the overall system cost. NPV is a useful metric for determining if an investment is worthwhile by examining costs and revenues over the life of the investment. Table 1 presents the NPV for each technology scenario and battery-price scenario. The optimization is able to dramatic increase NPV vis-à-vis the simple schedule, indicating the importance of optimal DER scheduling. In many cases it is able to generate a positive NPV for a technology portfolio which produced a negative NPV (loss on investment) when scheduled with the simple heuristic. This is especially true as system size and complexity grows (e.g. larger PV and storage installations). In absolute terms, optimization increases the value of the system by more than one million dollars (scenarios 7-9).

Table 1. DER capacity inputs and results summary by scenario (S1-S9).

Scenario	PV size [MW]	Battery size [MWh]	Battery power [MW]	Total annual savings	Annual savings percent	Load from PV	PV capacity factor	NPV high cost	NPV med cost	NPV low cost
base case	0	0	0	$0	0	0	NA	$0	$0	$0
S1	1	0	0	$296,012	20%	21%	100%	$444,000	$444,000	$444,000
S2	2	0	0	$545,752	33%	38%	100%	$316,000	$316,000	$316,000
S3	3	0	0	$715,620	38%	44%	89%	-$807,000	-$807,000	-$807,000
S4 - optimized	1	1	0.5	$353,734	23%	21%	100%	$158,000	$658,000	$958,000
S4 - simple	1	1	0.5	$303,700	20%	21%	100%	-$465,000	$35,000	$335,000
S5 - optimized	2	1	0.5	$609,761	37%	37%	100%	$109,000	$609,000	$909,000
S5 - simple	2	1	0.5	$558,776	34%	42%	100%	-$526,000	-$26,000	$274,000
S6 - optimized	3	1	0.5	$830,116	42%	43%	96%	-$385,000	$115,000	$415,000
S6 - simple	3	1	0.5	$786,803	40%	60%	96%	-$925,000	-$425,000	-$125,000
S7 - optimized	1	2	1	$380,723	25%	20%	100%	-$505,000	$495,000	$1,095,000
S7 - simple	1	2	1	$303,700	20%	21%	100%	-$1,465,000	-$465,000	$135,000
S8 - optimized	2	2	1	$642,106	40%	38%	100%	-$488,000	$512,000	$1,112,000
S8 - simple	2	2	1	$558,776	34%	42%	100%	-$1,526,000	-$526,000	$74,000
S9 - optimized	3	2	1	$878,871	45%	44%	98%	-$777,000	$223,000	$823,000
S9 - simple	3	2	1	$810,365	42%	61%	98%	-$1,631,000	-$631,000	-$31,000

Annual savings total and percent values are given to the no DER base case. PV capacity factors are given relative to the full output of same sized PV array, and consider both on-site use and export. Net present value calculations compare annual savings of DER use with amortized capital cost of installation over the assumed 20 year life of the equipment.

In addition to scheduling DER, DER-CAM is capable of selecting an optimal technology portfolio. To further assess the DER portfolios specified in each technology scenario, the same load, weather, and cost inputs are fed into the model, which is now allowed to select installed capacities. While DER-CAM is able to select from a diverse menu of technologies, this investigation limits the choices to PV and electric storage. Storage investment is constrained to discrete increments of 500 kWh. A summary of these results are given in Table 2. Note that the NPV of each of these cost scenarios are higher than any NPV for the same cost scenario in Table 1. In each case, the overall increase in NPV is small relative to the total, meaning that much of the benefit of optimization can be realized through controlling the DER scheduling without optimization of the portfolio. As storage costs drop, investment in both storage and PV increase.

Table 2. Optimal PV-storage capacity and NPV as generated by DER-CAM

scenario	PV size [MW]	Battery size [MWh]	NPV
high cost	0.69	0	$468,436
med. cost	1.04	1	$661,667
low cost	2.43	5	$1,300,604

CONCLUSIONS

From a review of recent studies, it is clear that the growth in distributed PV generation is positioned to accelerate rapidly over the next 5 to 10 years. This rapid increase in generation from an intermittent, schedule-independent source can create new issues or exacerbate existing problems faced by utilities and system operators, without supplemental technologies, either on the utility-side or behind the customer meter. Researchers at LBNL assert that the solution to this problem of distributed generation is distributed storage and control. Through the development of a supervisory controller, powered by the optimization tool DER-CAM, deployed at a real California facility, these researchers intend to demonstrate the economic benefits, both to customer and utility, of such a solution. This controller will contain planning and optimization capabilities to respond to a number of price signals, including tariffs and demand response events, and is subject to local technical and reliability constraints. The controller will also have functionality allowing it to communicate instructions to a site's DER in real-time, accounting for deviations from planned schedules.

To demonstrate the potential value of such a controller, a number of technology scenarios have been run through the annual investment & planning version of DER-CAM. The annual costs of these optimized schedules are compared to schedules determined by a simple heuristic. While the overall utilization of PV is comparable between the simple and optimized cases, the optimized schedules achieve consistently lower costs by managing demand charges and maximizing revenue from PV export. Over the assumed lifetime of the equipment, the net present value is significantly increased, in some cases by as much as $1,000,000. While the current high price of storage has a limiting effect on the economic viability of behind-the-meter PV-storage systems, optimized scheduling is able to produce systems with positive NPV, given other assumptions for system lifetime and interest rate. As the costs for electric storage fall, the economics for further deployment will improve, as evidenced by the medium and low cost scenario results.

ACKNOWLEDGEMENTS

DER-CAM has been funded partly by the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy under Contract No.

DE-AC02-05CH11231. The Distributed Energy Resources Customer Adoption Model (DER-CAM) has been designed at Lawrence Berkeley National Laboratory (LBNL).

REFERENCES

Brandt T. DeForest N. Stadler M. Neumann D. Designing an energy information system for microgrid operation. Working Paper. 2014

CAISO. California ISO fast facts. 2013. Available at <http://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf>

California Energy Commission. 2014. Developing advanced energy storage technology solutions to lower costs and achieve policy goals. Available at <http://www.energy.ca.gov/contracts/PON-13-302/ >

G. Cardoso, M. Stadler, A. Siddiqui, C. Marnay, N. DeForest, A. Barbosa-Póvoa, and P. Ferrão, "Microgrid reliability modeling and battery scheduling using stochastic linear programming," *Electric Power Systems Research,* vol. 103, pp. 61-69, 10// 2013.

N. DeForest, G. Mendes, M. Stadler, W. Feng, J. Lai, and C. Marnay, "Optimal deployment of thermal energy storage under diverse economic and climate conditions," *Applied Energy* 119 p 488–496. 2014.

Feldman D, Barbose G, Margolis R, Wiser R, Darghouth N, Goodrich A. US DOE SunShot. Photovoltaic (PV) pricing trends: historical, recent, and near-term projections. 2012.

Hanley C, Peek G, Boyes J, Klise G, Stein J, Ton D, Duong T. Technology development needs for integrated grid-connected PV systems and electric energy storage. In: 34th IEEE photovoltaic specialists conference; 2009. p. 1832–37.

Mammoli A, Stadler M, DeForest N, Barsun H, Burnett R, Marnay C. Software-as-a-service optimised scheduling of a solar-assisted hvac system with thermal storage. 3rd International Conference on Microgeneration and Related Technologies. April 2013.

Marnay C, Stadler M, Siddiqui A, DeForest N, Donadee J, Bhattacharya P, Lai J. Application of optimal building energy system selection and operation. Journal of Power and Energy 2013; 227;82-93.

Masters GM. Renewable and Efficient Electric Power Systems. John Wiley & Sons, Inc., Hoboken, NJ. 2004.

PG&E. Pacific Gas and Electric. Electric schedule E-20 tariff. 2014. Available at http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_E-20.pdf

Solar Energy Industries Association (SEIA). 2013. U.S. solar market insight report Q3 2013. Available at <http://www.greentechmedia.com/research/ussmi >.

Stadler M, Marnay C, Cardoso G, Lipman T, Mégel O, Ganguly S, Siddiqui A, Lai J. "The CO2 Abatement Potential of California's Mid-Sized Commercial Buildings," LBNL-3024E, 2009.